JOB FLOWS AND ESTABLISHMENT CHARACTERISTICS: VARIATIONS ACROSS U.S. METROPOLITAN AREAS

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Abstract:
This paper furthers the understanding of models with constant churning among heterogeneous agents by exploring the regional variation in gross job flows and establishment characteristics. Evidence across 53 Metropolitan Statistical Areas from a new source of microdata shows a positive relationship between regional employment growth and job turnover, with most regional differences occurring in job creation, and a strong negative relation between growth and the average age of establishments in a region. These relations persist even after controlling for regional differences in industry mix, and are all consistent with standard models of creative destruction.

The relations also persist after controlling for regional differences in establishment age distributions, however. Moreover, job destruction decreases as establishments age, and I find no clear negative relation between establishment entry rates and their exit ages. These patterns are *not* consistent with creative destruction models where firm vintage replacement drives job turnover, and instead suggest a turnover process seen in standard models of firm learning and selection. Further evidence suggests this turnover varies systematically with the overall employment growth of a region. Together, the results suggest that (i) models of labor dynamics need to highlight the turnover that occurs both within and between establishment ages, and (ii) environmental factors, such as the local "business climate", may affect the dynamics of this turnover.

Introduction

Recent empirical work on employment dynamics has focused on their gross rather than net flows. This work underscored the importance of acknowledging the heterogeneity and dynamics that underlie macroeconomic behavior. Research focused on the cyclical aspects of these dynamics. Studies also looked at their cross-sectional behavior—variations across industries, firm sizes, and firm ages are well documented.[1] However, very few studies document the cross-sectional variations across *regions*.[2] Unlike industry, size, or age definitions, regional differences can highlight variations across distinct labor markets. Thus, one could use regional evidence as a test of how theoretical models behave in different environments.[3]

In this paper, I detail the regional variations in employment dynamics across *metropolitan areas* using a new source of establishment microdata from the Bureau of Labor Statistics (BLS). Like countries, metropolitan areas arguably characterize distinct local economies. In addition, the data I use is rich enough to allow a detailed study across many metropolitan areas, providing ample variation across regions. My goal is to characterize new findings relevant to the broad classes of models stressing constant churning among heterogeneous agents. In particular, I focus the findings' relations to models involving processes of creative destruction or firm learning and selection. A first glance at the metropolitan data reveals three distinct findings. First, the net employment growth of an area is positively related to its job turnover. Second, most of the regional differences in job turnover stem from differences in job creation rather than job destruction. Third, net employment growth and the average age of establishments are negatively related across metropolitan areas. A decomposition exercise indicates regional differences in industry mix can only account for a portion of these results.

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[1] Davis and Haltiwanger (1999) provide an extensive review of this research.

[2] These studies include Eberts and Montgomery (1995), and Dumais, Ellison, and Glaeser (1997). Both are discussed in the following section.

[3] Ideally, one would want regional definitions that characterize separate economies. Studies across countries are appropriate, and there exists some work of this sort (see Baldwin, Dunne, and Haltiwanger,

These findings are suggestive of a creative destruction process, where key parameters, such as the rate of technology growth, broadly defined, may differ across regions.

A second decomposition breaks out regional differences in job flows by establishment age. Differences occur both within and age groups—regional differences in age distribution are only a portion of the explanation. A study of entering cohorts reveals that while entry and exit are higher in high-growth regions, their job turnover, particularly job destruction, decrease as entrants age[4]. In addition, there is no significant negative relation between the entry rate of an area and the age of its exiting establishments. These results contrast standard processes of creative destruction, and instead reveal several trends consistent with a process of firm learning and selection. Moreover, the *pace* of these dynamics varies across areas. Areas with higher employment growth have higher initial levels of job turnover among their entrants, but the rate of turnover decreases relatively faster in these areas. These findings suggest that some areas (notably those with higher employment growth) have intrinsic differences from other areas that may increase the pace of selection within a firm learning framework.

Taken together, the results across metropolitan areas imply that models wishing to fully characterize labor market dynamics need to address the employment dynamics that occur both within and across establishment ages. Models including processes of creative destruction *and* firm learning may succeed in this respect. In addition, these models must account for the intrinsic features of a labor market (e.g., local government policies, the skill composition of labor supply, entry costs, the general "business climate"), which can greatly affect the dynamics of these processes.

The following section provides a summary of the relevant empirical work, as well as a discussion of models that focus on creative destruction and firm learning processes. The data are

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1998). Some studies have cross-country comparisons, but not in an analytical framework (see Davis and Haltiwanger, 1999).

[4] These are also consistent with previous findings, such as those of Dunne, Roberts, and Samuelson (1988, 1989a, 1989b).

described next, followed by the basic findings across metropolitan areas. Analyses for industry, age, and entering cohorts come next. The proceeding section discusses intrinsic factors and that could affect the dynamics of the creative destruction and learning processes. The final section draws conclusions.

Background

There has been considerable research on the gross flows of employment. Davis and Haltiwanger (1990, 1992), and Davis, Haltiwanger, and Schuh (1996) provide the most extensive compilation of job flows and their heterogeneity across detailed industries, firm size, and firm age. Their work focuses on establishment data within Manufacturing. Dunne, Roberts, and Samuelson (1988, 1989a, 1989b) also focus on Manufacturing and document the patterns of firm growth, entry, and exit within and across detailed industries, firm sizes, and firm ages. Foote (1998) looks at firms within and outside of Manufacturing in Michigan and documents differences in the cyclical behavior of industries. Anderson and Meyer (1994) and Burgess, Lane, and Stevens (2000) study both job flows and worker flows across all industries. Work on regional job flows is limited. Several researchers have studied local labor market dynamics through the net growth of employment. Blanchard and Katz (1992) study wage, unemployment, and employment dynamics in response to adverse shocks to labor demand across U.S. States. Davis, Loungani, and Mahidhara (1997) have a similar study for State responses to defense and oil shocks. Glaeser, Kallal, Scheinkman, and Schleifer (1992) have a notable study on the dynamic spillover effects of industry agglomeration. Dumais, Ellison, and Glaeser (1997) have one of the few regional studies that appeal to firm-level dynamics within metropolitan areas. They look at how firm entry, exit, growth, and contraction relate to changes in regional industry concentration. Eberts and Montgomery (1995) also study firm dynamics across regions, documenting the cyclical versus secular trends in job flows.

The empirical work done with national-level data has led to a focus on dynamic models that stress constant churning among heterogeneous agents. Models of vintage replacement, or creative destruction, form one such class of models. Caballero and Hammour (1994) present a creative destruction model where firms continuously enter with the latest technology, and in a 1996 paper analyze the welfare consequences of this process. Aghion and Howitt (1992) present a model where a creative destruction process emerges via research innovations. In another model, Aghion and Howitt (1994) relate a creative destruction process to unemployment. Models of firm learning and selection also stress constant churning and heterogeneity. Jovanovic (1982) presents a model where firms learn their true efficiency over time from a signal involving firm-specific cost shocks. Hopenhayn (1992) produces a similar model from which he draws steady-state implications. Ericson and Pakes (1995) have a model of active learning where firms can endogenize the learning process through investment.

Several stylized facts about job flows emerge from the empirical work, which Davis and Haltiwanger (1999) summarize. I highlight the evidence relevant to this study. First, there is a tremendous turnover of jobs every period, whether one looks at quarterly, annual, or longer frequencies. Second, the rates of job turnover vary greatly across industries, firm sizes, and firm ages. In particular, Manufacturing tends to have the lowest job turnover, while seasonal industries, such as Construction and Retail, tend to have the highest. Job turnover decreases with both firm age and firm size, so the greatest turnover occurs in the youngest and smallest firms. Firm entry and exit also decrease with size and age. Third, there is tremendous heterogeneity in firm entry, exit, and growth outcomes even within industry, size, and age categorizations. Finally, studies find an inverse cyclical relation between turnover and net growth—over time, periods of high turnover occur when employment growth is lowest. Foote (1998), however, shows that this finding may be unique to declining industries. Eberts and Montgomery (1995) document a similar cyclical trend, but find a positive pattern across States—areas with high growth are also areas with high turnover.

Models of creative destruction operate through a vintage replacement process—new firms enter with the latest technology, replacing older, outdated firms. In equilibrium, there is continuous entry and exit, as well as a steady-state distribution of firm vintages. The rate of technology growth, broadly defined, determines the equilibrium dynamics. Higher rates of technology growth increase entry, exit, and job turnover. They do so by lowering the age at which outdated firms exit, creating a relatively younger distribution of firms. With respect to these models, this study tacitly assumes that regions can differ in technology growth.[5] These differences may stem from variations in the level of localized innovations, or in the amount of skilled labor[6]. I review these sources of variation in the Discussion. In models of firm learning, firms do not know their productive abilities *ex ante*, and must learn them over time from a noisy signal. Firms form an expectation on their ability from repeated realizations of this signal, and choose to either grow or exit based on it. Over time, inefficient firms exit, creating a selection process. For a given cohort, exit and job turnover are high early on, but decrease as the cohort ages. Exogenous factors can affect the dynamics of this process. Hopenhayn (1992) discusses how economies with lower entry costs or higher operating costs will have an accelerated selection process, and therefore greater turnover among relatively younger firms. Hopenhayn and Rogerson (1993) show how firing costs can decrease the incentives to hire and fire, thus decelerating the selection process. In the Discussion, I argue that regional differences in the business "climate" may affect the selection mechanism of a learning process. Local factors, such as public policies and infrastructure, the skill mix of labor, and localized information spillovers may increase the *pace* at which firms learn their true abilities.

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[5] The relation of a vintage replacement process to regional variations is not new. Varaiya and Wiseman (1978, 1981) have studies that attempt to relate the age of a metropolitan area to the growth of its Manufacturing employment.

[6] For example, Chari and Hopenhayn (1991) present a vintage replacement model where there are complimentarities between firm vintage and human capital.

Data

Access to a robust source of longitudinal establishment microdata is essential to this study. The data I employ come from the Longitudinal Database (LDB), a new source of establishment data created by the Bureau of Labor Statistics. The LDB is a linked set of unemployment insurance (UI) records from the ES-202 program of the BLS. As such, it is the universe of all establishments (private and public, spanning all industries) with employment covered under a State's UI program.[7] This coverage represents 98 percent of all employment, reported quarterly, with the self-employed and the military being the primary exceptions.[8] In the most recent quarter, the LDB included over 8 million UI records. For this paper, the term "establishment" refers to a distinct UI record.[9] The data include monthly employment and quarterly payroll figures for each establishment. Most importantly, the data are linked across quarters to provide a complete longitudinal history for all records in the database. Pivetz, Searson, and Spletzer (2001) provide a detailed description of the linkage process. This process is not perfect. The data-generation process is a three-step procedure. It involves a State-level collection of data (for UI tax purposes, not necessarily for economic research), data processing by the ES-202 program, and record linkage, also done within the ES-202 program. The last procedure involves the greatest risk of mismeasurement. At most levels of disaggregation, missed links can dramatically overstate job flows. Linkages may be absent for a variety of reasons, including changes in corporate ownership, firm restructuring, and UI account restructuring. I summarize these issues and my methodology for dealing with them in the appendix.

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[7] Several other studies have appealed to the LDB (in various stages of its development) for research purposes. They include Card and Krueger (1998); Spletzer (2000); and Faberman (2001, 2002).

[8] See U.S. Bureau of Labor Statistics, (2000), p. 536, for details of exclusions.

[9] This is not always accurate. Prior to 1992, no effort was made to force multi-establishment reporters to report UI data for each establishment. The Multiple Worksite Report was instituted to enforce this rule and

I employ a sample of private sector establishments in 53 Metropolitan Statistical Areas (MSA's) across five States. The scope of the LDB coupled with the attention required by data linkage issues make it difficult to study much more. Regardless, the current sample represents approximately 15 percent of all private employment and establishments in the U.S. It includes data from the metropolitan areas of Colorado, Michigan, North Carolina, Ohio, and Pennsylvania from March 1992 to March 2000.[10] The sample includes 1.43 million unique establishments. The average quarter has 14.8 million workers in approximately 796,000 active establishments. On average, MSA employment ranges from 24,000 (Jacksonville, NC) to 1.88 million (Philadelphia, PA-NJ). Table 1 reports quarterly summary statistics for my sample (derived from the LDB) and for the United States (derived from ES-202 macrodata.)

Methodology

I define job flows as employment changes due to establishment openings, closings, expansions, or contractions. In this study, "opening" establishments are those with positive employment in the current quarter of observation and either zero or missing employment reported for at least three prior quarters. Similarly, "closing" establishments are those with positive employment in the previous quarter and either zero or missing employment reported for three subsequent quarters. Expansions are net gains in employment at continuing establishments. Contractions are net losses in employment at continuing establishments. Job creation is the sum of jobs added at opening and continuing establishments. Job destruction is sum of jobs lost at closing and contracting establishments. Job turnover, or job reallocation, is the sum of job creation and job destruction. The rates of these statistics use the average of the current and previous quarters' employment levels as the denominator, just as in Davis, Haltiwanger and

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ease the transition for large reporters. Since 1992, states have implemented this report, leading to a more accurate definition of a UI record as an "establishment".

[10] The MSA's studied also include Primary Metropolitan Statistical Areas (PMSA's). If an MSA crosses State boundaries, its State affiliation is the location where the majority of its employment resides. For those MSA's who cross state boundaries outside the five states studied (namely Philadelphia, PA-NJ,

Schuh (1996). The employment growth rate is simply the difference between the job creation and job destruction rates. The paper reports both quarterly and annual job flows. Quarterly flows use the third-month employment, while annual flows use March employment.[11] I do not seasonally adjust the quarterly flows, though they exhibit considerable seasonality. Wages are the total quarterly payroll (deflated with the Consumer Price Index to 1992 dollars) divided by average employment. When wage growth statistics are reported, they are done in analogous manner to employment growth—i.e., the average of the previous and current quarter's wage is used as the denominator. Establishment characteristics include their size (in workers) and age (in quarters). An establishment's age is based on its initial date of UI liability. The age variable must deal with both missing and sometimes incorrect (at least for the purposes of measuring age) liability dates. I deal with these as best as possible, with my methodology contained in the appendix.

Results

I begin this section focusing on the relationships of the employment characteristics and job flows to employment growth. Table 2 lists the summary statistics for the entire sample, averaged across time. Employment grew at 0.6 percent quarterly, with total job reallocation of 13.9 percent. Job reallocation was 25 percent annually, indicating that 55 percent of quarterly reallocation was transitory. Wages were approximately $6,600 per quarter (in 1992 dollars) with quarterly growth of 0.5 percent. The average establishment had just over 18 workers and was approximately 10 years old.

Much of the following analysis focuses on the relation of establishment dynamics and characteristics to regional employment growth. Table 3 lists the coefficients from the regression of the MSA value of the listed variable (averaged across time) on the MSA's employment growth rate (also averaged across time) and the implied Pearson correlations. Job flows have quarterly

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PMSA; Cincinnati, OH-KY-IN PMSA, Steubenville-Weirton, OH-WV MSA, and Charlotte-Gastonia-Rock Hill, NC-SC MSA) the relevant data from the outlying states are appended to the existing sample.

and annual results reported. The regressions show a strong positive correlation between employment growth and job creation, with a correlation of 0.76 in the quarterly data and 0.90 in the annual data. Surprisingly, employment growth and *job destruction* also have a positive correlation, with values of 0.49 in the quarterly data and 0.36 in the annual data. Consequently, the correlations between employment growth and job reallocation are strong and positive as well. These findings are consistent with the across-State findings of Eberts and Montgomery (1995), and the across-industry results of Foote (1998) and Baldwin, Dunne, and Haltiwanger (1998). An MSA's wage is uncorrelated with its employment growth, but its wage growth has a correlation of 0.39. High-growth MSA's tend to have smaller establishments on average, but the correlation is not strong. High-growth MSA's also tend to have younger establishments on average, and the correlation between employment growth and establishment age is a robust -0.66. Thus, high-growth MSA's tend to have higher rates of both job creation and job destruction within relatively younger establishments. These findings are consistent with the standard models of creative destruction described in the previous section.

Accounting for Differences in Industry Composition

There is significant heterogeneity in job flows and establishment characteristics across industries, as Table 4 illustrates[12]. More seasonal industries, such as Agriculture, Construction, and Retail, exhibit relatively higher job turnover, and have smaller and younger establishments, while other industries, like Manufacturing, have very low job turnover in larger, older establishments. In addition, the regional and urban economics literature documents significant differences in regional industry representation (for example, see Ellison and Glaeser, 1997). Therefore, it is plausible that the correlations reported in Table 3 are merely artifacts of regional differences in industry composition. To explore this hypothesis, I recalculate the correlations after conditioning out the effects of industry. Let X_{ij} denote one of the variables listed in the first

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[11] Pinkston and Spletzer (2002) discuss the methodology used for creating annual statistics with the LDB.

column of Table 3 for the i^{th} industry in the j^{th} MSA. Let G_{ij} denote the employment growth rate similarly defined. Regressions controlling for the between-industry variation in each are

$$(1) \qquad \begin{aligned} X_{ij} &= \delta_i + \varepsilon_{ij} \\ G_{ij} &= \delta_i + \eta_{ij} \end{aligned}$$

where δ_i represents a four-digit industry effect, and ε_{ij} and η_{ij} are error terms. The MSA values of the left-hand side variables independent of industry (denoted $\tilde{x}_j$ and $\tilde{g}_j$) are simply weighted sums of the residuals[13]. The share of the unconditional correlation due to industry is one minus the ratio of the conditional correlation (i.e., the correlation between $\tilde{x}_j$ and $\tilde{g}_j$) and the unconditional correlation.

Table 5 presents the results of this decomposition. Job flows are both quarterly and annual. The distinction between the two periods is important for this exercise, since seasonal trends in the quarterly data vary widely by industry. Comparing the contributions of between-industry effects across the two frequencies shows that seasonal fluctuations give them considerably more weight in the quarterly data. Thus, it may be more constructive to focus on the annual job flow results of this exercise. The exercise conditions out 972 four-digit industries for the 53 MSA's.

Industry differences account for 43 percent of the quarterly correlation between quarterly MSA employment growth and job creation, but only 14 percent of their annual correlation. Industry differences more than explain regional differences in job destruction. The relation between employment growth and job destruction switches from positive to negative when industry differences are controlled for. The relation between growth and job reallocation remains positive, with industry differences accounting for 79 percent of their quarterly correlation, and 47 percent of their annual correlation. Industry differences account for nearly all (91 percent) of the

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[12] Similar across-industry findings appear in Anderson and Meyer (1994), Foote (1998), and Burgess, Lane, and Stevens (2000).

relation between a MSA's growth rate and the average size of its establishments. They account for a much smaller fraction (38 percent) of the relation between growth and average establishment age. In summary, industry differences account for a good deal of the relations observed between employment growth and job destruction and establishment size, but they account for much less of the relations between growth with establishment age, job creation, and overall job turnover.

Accounting for Differences in Age Distribution

Figure 1 illustrates the negative relation between job reallocation and establishment age, while Figure 2 illustrates the wide distribution of establishments across age categories. Consequently, as with industry, regional differences in job flows may be an artifact of differences in age distributions. Moreover, the models noted earlier have distinct implications for whether job flow variations should be primarily a between or within age-category phenomenon. Creative destruction models contain a vintage replacement process that creates differences in job reallocation primarily through differences in establishment age distributions (i.e., between-age variations.) In contrast, firm learning processes stress job turnover *within* a given age category, as firms within a given cohort respond to the uncertainty created by firm-level shocks to production. The evidence thus far (i.e., high-growth areas with higher job turnover within relatively younger establishments) favors a creative destruction process. If between-age differences accounted for the relations seen in Table 3, it would lend further support to this process. If, however, most job flow relations were independent of age, then one would need to explore processes such as firm learning, which stress job turnover within age cohorts.

I categorize the sample by age and perform an analysis identical to the industry decomposition[14]. Rather than 972 four-digit industries, the decomposition uses 16 age

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[13] Residuals will either be weighted by employment (growth and job flows) or establishments (size and age), depending on the variable in question.

[14] I use an age measure unadjusted for state-level differences. This measure differs from that used in the previous sections. The adjusted measure (discussed in the appendix) distorts the age distribution within an

categories.[15] Results of the decomposition are in Table 6. Between-age differences account for 43 percent of the quarterly correlation between MSA employment growth and job creation, but only 22 percent of the annual correlation. Like with industry differences, age-distribution differences over-account for the relations between employment growth and job destruction, with the quarterly correlation essentially zero, and the annual correlation -0.49. Variations in the age distribution account for 65 percent of the quarterly correlation between employment growth and job reallocation and 76 percent of their annual correlation. These findings are generally supportive of the vintage replacement process seen in creative destruction models, but enough of the within-age category relation between growth and turnover remains (between one-quarter and one-third) that it warrants a further exploration of its causes.

Entering Cohort Analysis

I explore within-age differences in job flows with an analysis of entering establishments. The following exercise focuses on entry, exit, growth, and job flow evidence for the first five years of an entering cohort's existence. Establishments enter between the second quarters of 1993 and 1995, providing nine distinct cohorts. Pooled together, they represent 177,373 starting establishments, making up 2.5 percent of active establishments and 0.7 percent of employment in a given quarter. I have 2,472,713 distinct observations on these entrants. I take extra care to ensure that the entrants are true births and not the re-opening of existing establishments.

Table 7 presents the sample means and correlations for various cohort statistics. The statistics are for the pooled sample of entrants within a particular MSA. The entry rate of establishments represents 2.5 of all establishments in a quarter, but *half* of these entrants exit within their first five years of existence. Those that exit do so in less than two years, on average.

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area, making it incompatible with this exercise. Also, I deal with changes in UI account structures differently than what is described in the appendix. I account for these changes at the quarter-MSA-age category level instead of the quarter-MSA-4-digit industry level. Issues related to age measurement cause large changes across age categories that I cannot account for. This makes estimates of job flows are somewhat higher.

Total employment for each cohort declines over the first five years, but surviving establishments grow 26 percent in this period. The average wage of the cohort grows 20 percent. Entrants begin with 46 percent lower wages than the average wage for their MSA. After five years, their wage is only 17 percent lower. The first column of correlations represents the across-MSA correlation with the variable in the leftmost column with the MSA (total, not just the cohort) employment growth rate. The next two columns report the correlations with the entrants' share of MSA establishments and the average age of exiting establishments, respectively. The rates of both entry and exit are higher in MSA's with high employment growth. The age of exiting establishments, comparable to the "scrapping age" in creative destruction models, is somewhat lower in these MSA's, but the correlation is not significant. As on might expect, cohort employment growth and surviving establishment growth are both positively correlated with MSA employment growth. Consistent with a vintage replacement process, entry and exit rates have a strong positive correlation of 0.57. Entry and the exit age, however, are unrelated. This is in contrast to the vintage replacement process, in which higher entry and a younger exit age occur together via a higher rate of technological change. MSA's with higher entry rates tend to have higher growth for their cohorts and their cohorts' survivors, in particular. In addition, MSA cohorts with higher overall and survivor growth had exits occur at a younger age, on average. Thus, while the overall relation between entry (or growth) and the exit age is essentially zero, the relation between cohort and survivor growth and the exit age is significantly negative. This may be consistent with regional differences in a firm learning process, and I discuss how so in the following section.

Cohort wage growth is positively correlated with both the entry rate and MSA employment growth. The wage an establishment begins with (relative to the MSA wage) is independent of both MSA growth and the entry rate, but the wages offered by those who survive

[15] These categories group establishments by age at one-year intervals for ages 0 to 10 years and at two-year intervals for ages 10 to 20 years. A final category includes establishments 20 years and older.

5 years (relative to the MSA wage) is positively related to both. None of the wage statistics are significantly related to the average exit age of establishments.

In my final exercise, I explore the relation between job flows, establishment age, and MSA employment growth through establishment-level regressions with the pooled sample of entrants. In doing so, I hope to see whether (i) job flows decrease with age, which would be consistent with firm learning, but inconsistent with vintage replacement[16], (ii) the job flow-age relation varies across metropolitan areas, and if so, (iii) what the pattern of this variation may be. The pooled sample includes 2,472,713 observations on the 177,373 entrants. The dependent variable is either the job creation, job destruction, or job reallocation rate. At the establishment level, job creation is the net employment change given a positive gain, while job destruction is the net employment change given a loss. Job reallocation is the absolute value of the net employment change. Let Y^c_{eijt} be one of these variables for establishment *e* in cohort *c* in industry *i* in MSA *j* aged *t* quarters. The full regression specification is

(2) $$Y^s_{eijt} = \alpha^c + \mu_q + \beta G_j + \gamma_t D_{et} + \delta_i + \eta_t \left[D_{et} \cdot G_j \right] + \varepsilon^c_{eijt} .$$

The α^c control for cohort entry quarter, while the μ_q are quarter dummies that control for seasonal effects. The average quarterly MSA employment growth rate is G_j, the γ_t are age fixed effects, the δ_i are 4-digit industry effects and the η_t are coefficients from the interaction of the age effects with the MSA growth rate. I weight regressions by employment levels. Using this regression, I can obtain the fitted age-job flow relation for an MSA with average growth rate $\overline{G}_j$. Conditioning out cohort, season, and industry effects makes the fitted value

(3) $$\hat{\hat{Y}}_{jt} = \hat{\beta}\overline{G}_j + \hat{\gamma}_t + \hat{\eta}_t \overline{G}_j .$$

Figures 3 through 6 map out the $\hat{\hat{Y}}_{jt}$ over the five-year period using a centered 3×3 moving-average trend—this smoothes out any seasonality remaining after controlling for quarter-of-the-year. In all tables, two trends are fitted with G_j equal to 1.15 and 0.23 percent—these correspond to the MSA growth rates in the 90^{th} and 10^{th} percentiles, respectively. Figure 3 shows the relation between job reallocation and establishment age before I control for industry. Figures 4 through 6 depict the trend for the full regression specification (industry effects included) for job reallocation, job creation, and job destruction, respectively. The interaction coefficients, $\hat{\eta}_t$, and their significance for the latter three figures are reported in Table A.2 of the appendix.

Figure 3 shows job reallocation clearly decreases with age. The trends for a high-growth versus low-growth MSA show an interesting twist on this relation. Job reallocation begins higher among entrants in high-growth areas. This is not too surprising, given the positive relations between MSA growth and reallocation seen in the beginning of this section. As cohorts age, however, the rate of reallocation decreases *faster* in the high-growth areas. By the fourth year, there is no significant difference in job reallocation between high and low-growth areas. In fact, the graph shows a crossing-point towards the end of the period, where the low-growth areas have higher turnover—the interaction coefficients for these later quarters are insignificant, though. Figure 4 controls for industry effects and shows a qualitatively identical result. The only notable difference is the earlier occurrence of the crossing-point of the two trends, which happens about two years after entry. Figure 5 again portrays a qualitatively similar result, but this time for job creation. Job creation among entrants is greater in high-growth MSA's for the first two to three years of existence, but this difference dissipates by the fourth year. It is not until Figure 6 that a different trend is portrayed. Job destruction still decreases with age, and I should note that this again contrasts with a vintage replacement process, but is consistent with firm learning. Job destruction, however, is higher within the low-growth MSA's. The difference in slopes of the two trends is not nearly as distinct as with job reallocation or job creation. The difference in

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[16] This would also be consistent with the findings of Dunne, Roberts, and Samuelson (1989a, 1989b).

levels, however is significantly greater in the low-growth areas.[17] Thus, there are region-specific factors that not only affect the rates of establishment entry and growth, but their dynamics as well. Given the evidence in Figures 5 and 6, it seems that these effects are relatively more important for job creation rather than job destruction.

Discussion

The above findings begin with strong evidence of a creative destruction process—areas with high employment growth have higher turnover among relatively younger establishments. These areas have higher entry and exit, and between-age differences account for much of the relation between job turnover and regional growth. Underlying the relation between these findings and models of creative destruction is an assumption that high employment growth areas are also high technology growth areas, broadly defined. The results in this study do not explicitly illustrate regional variations in technology growth, yet the assumption is plausible. Under standard neoclassical assumptions, wage growth is a proxy for the growth of labor productivity, and it is positively correlated with employment growth in the results above. Using evidence from patent citations, Jaffe, Trajtenberg, and Henderson (1993) show that innovations are localized within metropolitan areas, and that the spatial diffusion of these innovations is slow. A slow diffusion of ideas would lead to persistent regional differences in innovation, and imply that the initial results above would be consistent with the creative destruction model presented by Aghion and Howitt (1992). Finally, the level human capital varies across areas. Table 8 presents statistics compiled from the 2000 decennial census and shows that a younger, more educated labor force is positively correlated with both growth and job turnover, and negatively correlated with establishment age. These are exactly the relations one would expect were the level of technological change to vary in the vintage human capital model of Chari and Hopenhayn (1991).

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[17] The coefficient on growth for this regression $\hat{\beta}$ is -1.27 with a standard error of 0.30, and corresponds with the coefficients in the final column of Table A.2.

There are also some results that conflict with standard models of creative destruction. Job destruction decreases rather than increases with age, and there is no clear positive relation between establishment entry rates and their average exit age. In addition, between one-quarter and one-third of the growth-reallocation relation cannot be explained by regional between-age variations. Many characteristics of entering establishments are instead consistent with a firm learning process, particularly those related to the establishment age-reallocation relationship. Also, the dynamics of this relationship seems to vary systematically in its *pace*—high-growth metropolitan areas have greater job turnover among their youngest establishments, and this turnover declines with age *faster* than in other areas. As mentioned earlier, Hopenhayn (1992) shows how exogenous factors, such as entry costs and operating costs, can lead to changes in the selection process, while Hopenhayn and Rogerson (1993) show how high firing costs can decrease turnover and employment growth. Differences in firing costs are generally an across-country concept, but one could think of a greater union presence in an area as a barrier to job destruction. Table 9 presents growth, turnover, and union membership for the five States in this study, the lowest level of regional detail for which union data is available. The evidence is weak, and more aggregated than the other results of this study, but there is a somewhat negative trend between employment growth and union membership among the five States.

I further propose that variations in the pace of selection could arise from regional differences in the "noisiness" of the firm-level shock. Differences in business "climate" may create this variation. These differences could stem from differences in public infrastructure, access to capital markets, the local skill mix, local product market competition, or information spillovers stemming from firm agglomeration. These suggestions are purely speculative, but regional differences in the pace at which firms learn would match the regional variations in the age-reallocation relationship observed within entering cohorts. Figure 7 replicates the dynamics depicted by Jovanovic (1982, p. 650), but does so for two economies—one with a noisy learning process and one with a relatively smooth learning process. The figure illustrates the behavior of a high and low-productivity firm within each economy. The thin lines represent their behavior within a noisy learning environment, while the thick lines represent their behavior in the smooth learning environment. When learning is less noisy, firm beliefs converge to their true value faster. The growth of productive firms and the exit of less successful firms occur quicker. This implies that turnover will be higher in the smoother learning environments among the youngest firms, but that this turnover will decrease faster as firms age in these environments. This is exactly the trend in job reallocation depicted in Figures 3 and 4.

Conclusions

This study presents new results for job flows and establishment characteristics across metropolitan areas using a new, rich source of establishment data. I find that both job turnover and the age distribution of establishments are strongly related to the employment growth of a region—high-growth areas have higher turnover within relatively younger establishments. Differences in turnover are due more to differences in job creation rather than job destruction. These results persist even after controlling for regional differences in industry composition. The results give strong support to a model of creative destruction, but a decomposition by establishment age indicates between one-quarter and one-third of the relation between job reallocation and growth are independent of the age distribution. In addition, a study of entering cohorts shows that while high entry and exit rates tend to coexist within high-growth areas, there is no clear relation between entry rates and the average age of exiting establishments, and that job destruction decreases rather than increases with age. These findings run counter to a model of creative destruction, and indicate that a model of employment dynamics needs to account for turnover independent of age in addition to a creative destruction process. The turnover related to a firm learning process is consistent with my findings for entering establishments.

The evidence for entrants also suggests that regions may vary in the *pace* of firm learning. Job reallocation begins higher and declines faster as establishments age in high-growth areas. Thus, the turnover that occurs independent of establishment age varies systematically with the overall employment growth of the metropolitan area. Were a learning model accepted as the proper characterization of this turnover, its variation suggests that region-specific factors (entry costs, labor skill mix, business climate) affect its dynamics in much the same way that exogenous factors, such as the rates of technology or productivity growth, are thought to affect the dynamics of a vintage replacement process.

Appendix

Data Overview

The longitudinal nature of the LDB is its most important feature, making the linkage process very important. Before linkage, the data is nothing more than a collection of records from the ES-202 program. These records use three primary variables as identifiers: the state code, a ten-digit UI account number and a three-digit Reporting Unit Number (RUN). Within each state, a UI account is given to one or more establishments. The assignment is done with the intent of a UI account roughly corresponding to the definition of a firm. If a UI account has more than one establishment, different RUN's are assigned to each. In addition, a federal identifier is assigned to each UI account. The Employer Identification Number (EIN) is a nine-digit number assigned for the tracking of multi-state firms. A firm operating in several states will have different UI numbers in each state, but will have only one EIN. Together, these identifiers provide a structure for the linkage of records across quarters. The linkage process assigns an LDB Number to each record. Multiple establishments within a UI account each get a unique number. Further checks (discussed in detail in Pivetz, Searson, and Spletzer, 2001) are then applied to make the linkage process more accurate.

Linkage and Measurement Issues

As a consequence of the LDB's scope, data discrepancies often arise[18]. The most common data issue is not an error at all, but the purposeful breakout or consolidation of records within a UI account. BLS has continuously made efforts to improve data quality for the LDB, particularly for data reporting. The use of the Multiple Worksite Report has gone far in improving the accuracy of reporting multi-establishment accounts. As employers improve their reporting techniques, they often restructure the number of records in their UI account. Breakouts split employment from one record to many records. In this case, the original record was not a true single establishment, but multiple establishments that a firm lumped together for reporting purposes. Consolidations do the opposite. Ideally, every establishment would have its own UI record (and hence its own LDB number). However, sometimes BLS requires the consolidation of several records[19].

Breakouts and consolidations are accounting changes, and not economic changes. A reshuffling of workers to new locations, a change in corporate ownership, or an opportunity to restructure the UI account for tax purposes can also lead to changes in an UI account. Identifiers called predecessor and successor flags identify all account restructuring, regardless of how it comes about. The predecessor flag identifies when a record ends, but is not a true closure. A separate variable identifies the UI account of the new record(s). Successor flags identify new records that are not true openings. A separate variable identifies the UI account number of the original record(s). Broken out and consolidated records have unique LDB numbers, even though they are technically continuous establishments. Given that not all breakouts and consolidations are adjustments in data reporting, BLS keeps these records separate, letting researchers use the predecessor and successor information at their discretion. Also, not all linkages are accounted for

[18] Davis and Haltiwanger (1998) provide a general summary of the advantages and disadvantages of working with UI records.
[19] This generally involves very small establishments with less than 10 workers.

in the data. Many factors can lead to the overlooking of record linkages. Missing record links overstate the number of establishments opening and closing. While the net changes in employment remain unaffected by this problem, the rates of job creation and job destruction are over-estimated.

The Unemployment Insurance program has tax consequences for reporting employers. This can affect the way employers report their UI liabilities (i.e., their employment and payroll data). For example, an employer may be better off reporting all of his establishments in one account, or perhaps creating separate accounts for each establishment, even though they all belong to the same firm. The tax structures of UI programs vary by state, implying the behavioral response of employers varies as well. There is no direct way to deal with this phenomenon, but it cannot be overlooked in a multi-state study. It can cause systematic measurement error in some observed economic variables, particularly with their across-state variation. Establishment size and establishment age are at the greatest risk of mismeasurement. Either variable may be either over or under-biased, based on the specific tax incentives.

Dealing With Linkage Issues

Accounting for missing record linkages is the most imperative of all data issues. Once the data are linked correctly, other issues can be better addressed. Unfortunately, there is no ideal solution to matching or even identifying unlinked records in the data. As one might guess, the linking algorithm used by BLS takes care of the simple links to identify, leaving only the most difficult and obscure cases unaccounted for. Knowing this, I attempt to rectify linkage issues for only the largest discrepancies. In doing so, I perform a rudimentary “grid search” on the microdata. While this sounds as though it will leave an overestimate of job flows within smaller establishments, I feel it is justified for the following reasons. First, most restructuring occurs in larger UI accounts, and thus larger establishments. Second, the number of establishments (or UI accounts for that matter) that have linkage issues is extremely small for any given quarter. However, given the average size of the establishments involved, the effects on employment dynamics are quite large. Third, job turnover at small establishments is already quite high[20]—the size-turnover trend observed in this data set is no different than the one observed in other sources, so any "cleaning" of these smaller records would have a negligible effect. Lastly, the process used to detect missing links ends up identifying large-scale problems with establishments of all sizes. For example, if a large bank restructures its account from a single record to records for each of its branches, the linkage check will identify both the successor relationship of the large record and the predecessor relationship of all the small branches. In this sense, only unreported linkages from small establishments to small establishments, and then only on a small scale, would go unnoticed.

I begin my linkage identification by processing the data and calculating job flows as if the data were correct, one state at a time (UI accounts are state-specific.) Next, I break the estimates out by quarter, MSA, and one-digit SIC[21]. I analyze the rates of establishment openings, closings, expansions, and contractions and note any "spikes" in their rates[22]. This identifies any large-scale linkage issues independent of establishment size. Next, I search the data for individual large establishments with possible linkage issues. Any establishment with an opening, closing, expansion, or contraction of at least 300 workers in a quarter is noted. I cross-

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[20] See Davis, Haltiwanger, and Schuh (1996) and Davis and Haltiwanger (1999) for documented evidence

[21] During the course of this process, I discovered several linkage issues that were either state-specific or LDB-specific. The former included cases with Michigan and Ohio. In Michigan, many establishment births were held until the fourth quarter for 1999. This obviously has a large effect on the timing and magnitude of estimated job creation and destruction. I account for this problem by assigning a random quarter of birth to each entrant in 1999:4, with probability weights equal to each quarter's average share of births during all other years in the sample. Once this was done, the employment and wages were imputed back to the assigned quarter and job flows were calculated accordingly. Ohio and the LDB as a whole encountered a simpler but more widespread problem. In Ohio during 1992:2 and 1993:1, and in all states in 1998:1, there was a spurious spike for establishment births and deaths. These spikes stemmed from statewide (or in 1998:1, nationwide) restructuring in the RUN's assigned within UI accounts. Units were given new LDB numbers and not assigned predecessor or successor flags when in fact they were continuous units. Flagging all multi-unit records with both establishment openings and closings rectified the problem, causing them to be treated as any other predecessor-successor relationship. The one drawback from this procedure is that it over-accounts for the linkage error and may assign flags to true births and deaths. The net change in employment among these flagged establishments are added in during the calculation of job flows, but the gross flows are ignored, giving only a lower bound measure of job creation and destruction within this group.

reference all noted discrepancies and then search through the microdata across the quarter-MSA-industry cells where problems were identified. I use an array of variables, including county and 4-digit SIC codes, UI and EIN numbers, employment, and payrolls. In most cases, pinpointing a linkage problem to the county-4-digit level identifies it quickly. In cases where I could produce no match, I allowed the discrepancy to stand—large discrete changes can also be legitimate. In some cases where very large discrepancies remained, I appealed to the complete LDB universe (not just my sample). In doing so, I used the records' predecessor and successor UI numbers, as well as the establishment's name to find a match.

I added flags to identify all records I had identified a link for. In cases of what BLS defines as "partial breakouts", employment and wages would often have to be imputed for one or more records before flagging them[23]. I then recalculated job flow estimates. I made a final attempt at identifying links for any remaining large discrepancies, and if successful, I flagged the relevant records and recalculated the estimates a final time.

Dealing with Measurement Issues for Age and Size

Establishment age comes from a UI record's "Initial Date of Liability". This variable is missing for a sizable minority of establishments. In addition, some establishments had liability dates that were clearly incorrect, at least for the purposes of measuring age (e.g., liability dates of June 2001 for establishments in the sample during 1992). I have two procedures for dealing with missing values. Before employing either, I set incorrect values to missing values. If an establishment opened during the sample period, I simply noted the first quarter in which they entered. If an establishment entered the sample as continuous record, I assumed an age equal to

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[22] Spikes are defined as at least a doubling of the trend rate for openings and closings, and at least a 50 percent increase in the trend rate for expansions and contractions, for any given cell.

[23] In a partial breakout, one record is split out into many records. However, the reporting of the original record does not cease. Instead, it acts as though it is one of the new, broken-out, records. In these cases, for reasons related to the original linkage algorithm, the employment and payroll data is withheld for a quarter in the new records, often causing a sharp drop in the employment of this UI account in the time series. To account for these partial breakouts, not only do I link the continuing and new records, but I also

the mean age of establishments with reported age data in 1992:1 within that establishment's state. The incidence of missing values decreases over time, due to the exit of establishments with missing data, coupled with increased reporting quality over time. This implies there may be a selection bias which distorts the true time trend of the average establishment age. Use of the mean age in 1992:1 as an imputation should mitigate this bias. To check if this is so, I performed a sensitivity analysis of the time trend to a variety of other imputed ages. Ages as little as two years different from the mean age distorted the age trend so much that I had to conclude they were doing more harm than good in accounting for this bias. Therefore, I am confident that the use of the mean age in 1992:1 as an imputation for establishments continuing through the beginning of the sample is the best approach in dealing with the bias. Note that there is no reason to suspect the bias would vary across industries or across areas (at least within states), so cross-sectional analyses should remain unhindered.

Due to differences in state tax laws, there may exist across-state differences in how firms report their data, leading to spurious variations in the calculation of the some statistics, particularly establishment size and age. I conditioned out state-level variations in these variables to account for this. However, the crux of the paper analyzes regional variations. To maintain a significant amount of regional variation in my data, I had to choose states with multiple MSA's. This retained the across-MSA variation that the empirical analysis appeals to, while removing variations that are only state specific. The labor intensity required of large states restricted me from merely choosing the largest states, and the need for data for an entire state when accounting for these spurious differences prevented me from merely looking at the largest MSA's across the country. The five states used in this sample are all relatively large, ranging from 1.3 million to 4.3 million workers in the average quarter, and all have between 7 and 14 MSA's. Thus, I am confident in the results I obtain from the remaining across-MSA variation. I run fixed effects

impute the missing quarter's employment and payroll by using the following quarter's data. This eliminates the break in the time-series and establishes the correct link.

regressions with age and size as dependent variables. Each variable has a separate regression run for each quarter, and the regressions use all observations in the five states, not just those in metropolitan areas. The regressors are fixed effects for states and four-digit industries; the latter are controls for across-state differences in industry composition. I obtain the state effects for each variable by quarter and subtract them out from the original value. I then proceed with my analysis using the adjusted values of adjusted establishment age and size. Note that for the within-cohort analysis, this adjustment process is irrelevant. I use other techniques to identify true births (which all have an age of zero at entry), and eliminate any observations that went through UI accounting changes throughout their life.

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TABLE 1.
SUMMARY STATISTICS: LDB SAMPLE AND U.S. TOTALS, PRIVATE SECTOR EMPLOYMENT

	LDB Sample		***United States***	
Variable	**Mean**	**Std. Deviation**	**Mean**	**Std. Deviation**
Employment (thousands)	14,798	---	99,148	---
Employment growth rate (percent)	0.58	1.95	0.67	1.81
Wages (1992 dollars)	$ 6,625	350	$ 6,470	369
Wage growth rate (percent)	0.48	7.27	0.51	7.65

Notes: Sample statistics represent the quarterly means and standard deviations from March 1992 to March 2000. Results for the LDB sample are for all private employment in the metropolitan statistical areas of Colorado, Michigan, North Carolina, Ohio, and Pennsylvania. Results for the United States are from aggregate tabulations of ES-202 data.

TABLE 2.
SUMMARY STATISTICS: LDB SAMPLE

	Quarterly Tabulations		***Annual Tabulations***	
Variable	**Mean**	**Std. Deviation**	**Mean**	**Std. Deviation**
Employment (thousands)	14,798	---	14,521	---
Employment growth rate (percent)	0.58	2.05	2.2	0.73
Wages (1992 dollars)	$6,625	350	6,594	355
Wage growth rate (percent)	0.48	7.27	1.9	2.98
Job creation rate (percent)	7.25	1.00	13.6	0.34
Job destruction rate (percent)	6.67	1.14	11.4	0.47
Job reallocation rate (percent)	13.92	0.91	25.0	0.38
Average establishment size (in workers)	18.8	0.27	17.7	0.21
Average establishment age (in quarters)	43.5	1.74	40.8	1.68

Notes: Quarterly and annual means are from March1992 to March 2000, for the full sample of metropolitan areas. Annual statistics represent the March to March employment dynamics and establishment sizes and ages as of March of the given year. Annual reporting of wages and establishment age is kept in quarterly values. Results are not seasonally adjusted.

TABLE 3.

RELATIONS BETWEEN LABOR MARKET CHARACTERISTICS AND EMPLOYMENT GROWTH

Independent Variable	Coefficient on Growth	R^2	Implied Correlation
Job Creation Rate (Quarterly)	1.894** (0.226)	0.58	0.76**
Job Creation Rate (Annual)	1.242** (0.087)	0.80	0.90**
Job Destruction Rate (Quarterly)	0.894** (0.226)	0.24	0.49**
Job Destruction Rate (Annual)	0.242** (0.087)	0.13	0.36**
Job Reallocation Rate (Quarterly)	2.789** (0.451)	0.43	0.65**
Job Reallocation Rate (Annual)	1.485** (0.173)	0.58	0.77**
Wages (1992 Dollars)	-247.0 (354.6)	0.01	-0.09
Wage Growth Rate	0.265** (0.089)	0.15	0.39**
Average Establishment Size	-1.880* (0.838)	0.09	-0.30*
Average Establishment Age	-5.625** (0.906)	0.43	-0.66**

N = 53

NOTES: RESULTS ARE FROM REGRESSIONS OF THE LISTED VARIABLE ON THE NET EMPLOYMENT GROWTH RATE. VARIABLES REPRESENT THEIR QUARTERLY OR ANNUAL AVERAGES (FROM MARCH 1992 TO MARCH 2000) FOR 53 MSA'S. STANDARD ERRORS ARE IN PARENTHESES.
** DENOTES SIGNIFICANCE AT THE 1 PERCENT LEVEL. * DENOTES SIGNIFICANCE AT THE 5 PERCENT LEVEL.

TABLE 4.

JOB FLOWS AND ESTABLISHMENT CHARACTERISTICS BY ONE-DIGIT INDUSTRY, QUARTERLY AVERAGES

Industry	Employment (thousands)	Employment Growth	Job Creation	Job Destruction	Job Reallocation	Average Establishment Size	Average Establishment Age
Agriculture, Forestry, and Fishing	143.5	1.3 (20.9)	18.8 (12.0)	17.5 (9.79)	36.3 (6.52)	8.7 (0.76)	36.7 (2.09)
Mining	29.1	-0.6 (4.04)	7.0 (2.26)	7.6 (2.62)	14.6 (2.77)	16.3 (0.59)	49.3 (4.19)
Construction	747.4	1.4 (8.17)	13.8 (5.19)	12.4 (3.48)	26.2 (3.36)	9.1 (0.54)	39.2 (1.32)
Manufacturing	3,278.6	0.06 (0.84)	4.2 (0.56)	4.1 (0.68)	8.3 (0.92)	56.8 (0.54)	57.6 (4.31)
Transportation & Utilities	838.3	0.6 (1.46)	5.9 (0.64)	5.3 (1.22)	11.3 (1.30)	29.0 (0.46)	41.5 (0.80)
Wholesale Trade	915.7	0.5 (1.05)	6.3 (0.53)	5.8 (0.90)	12.0 (1.04)	12.5 (0.35)	47.1 (2.53)
Retail Trade	3,171.9	0.5 (4.13)	8.6 (1.93)	8.1 (2.48)	16.7 (1.66)	17.6 (0.53)	41.2 (1.96)
Finance, Insurance, and Real Estate	974.6	0.4 (1.14)	5.8 (0.86)	5.4 (0.93)	11.2 (1.38)	14.2 (0.38)	47.2 (0.91)
Services	4,698.8	0.9 (1.40)	7.8 (1.00)	6.9 (0.66)	14.7 (0.96)	17.0 (0.40)	42.2 (1.47)

Notes: Statistics are tabulated from the full sample of metropolitan areas. Standard deviations are in parentheses. All statistics represent quarterly averages from March 1992 to March 2000.

TABLE 5.

ACROSS-MSA CORRELATIONS WITH EMPLOYMENT GROWTH, ACCOUNTING FOR INDUSTRY

Variable	*Correlations*		Percent of Correlation Due to Industry
	Unconditional	Independent of Industry	
Job Creation Rate (Quarterly)	0.76**	0.44**	42.7
Job Creation Rate (Annual)	0.90**	0.78**	13.5
Job Destruction Rate (Quarterly)	0.49**	-0.21	142.8
Job Destruction Rate (Annual)	0.36**	-0.31*	185.2
Job Reallocation Rate (Quarterly)	0.65**	0.14	79.2
Job Reallocation Rate (Annual)	0.77**	0.41**	46.7
Average Establishment Size	-0.30*	-0.03	90.5
Average Establishment Age	-0.66**	-0.40**	37.8

N = 53

NOTES: RESULTS ARE THE PEARSON CORRELATIONS OF THE LISTED VARIABLE WITH THE ON THE NET EMPLOYMENT GROWTH RATE. VARIABLES REPRESENT THEIR QUARTERLY OR ANNUAL AVERAGES (FROM MARCH 1992 TO MARCH 2000) FOR 53 MSA'S. CORRELATIONS INDEPENDENT OF 972 4-DIGIT INDUSTRY EFFECTS ARE OBTAINED THROUGH THE METHODOLOGY DESCRIBED IN THE TEXT.

** denotes significance at the 1 percent level. * denotes significance at the 5 percent level.

TABLE 6.

ACROSS-MSA CORRELATIONS WITH EMPLOYMENT GROWTH, ACCOUNTING FOR AGE

Variable	Correlations: Unconditional	Correlations: Independent of Age	Percent of Correlation Due to Age
Job Creation Rate (Quarterly)	0.74**	0.42**	43.2
Job Creation Rate (Annual)	0.87**	0.68**	22.2
Job Destruction Rate (Quarterly)	0.45**	-0.01	101.7
Job Destruction Rate (Annual)	0.27	-0.49**	285.6
Job Reallocation Rate (Quarterly)	0.62**	0.22	64.5
Job Reallocation Rate (Annual)	0.71**	0.17	75.9

N = 53

NOTES: RESULTS ARE THE PEARSON CORRELATIONS OF THE LISTED VARIABLE WITH THE ON THE NET EMPLOYMENT GROWTH RATE. VARIABLES REPRESENT THEIR QUARTERLY AVERAGES (FROM MARCH 1992 TO MARCH 2000) FOR 53 MSA'S. CORRELATIONS INDEPENDENT OF 16 AGE CATEGORY EFFECTS ARE OBTAINED THROUGH THE METHODOLOGY DESCRIBED IN THE TEXT.
** DENOTES SIGNIFICANCE AT THE 1 PERCENT LEVEL. * DENOTES SIGNIFICANCE AT THE 5 PERCENT LEVEL.

TABLE 7.

ACROSS-MSA CORRELATIONS OF ENTERING COHORT STATISTICS

	Sample Mean	Correlation with…: MSA Net Growth	Correlation with…: Entrant Share	Correlation with…: Exit Age
Entrant's share of MSA establishments (percent)	2.49 (0.44)	0.82** [0.000]	1.00 [---]	0.06 [0.655]
Share of entrants exited after 5 years (percent)	49.5 (2.48)	0.33* [0.017]	0.57** [0.000]	0.20 [0.155]

Average establishment age at exit (quarters)	7.82 (0.30)	-0.15 [0.284]	0.06 [0.655]	1.00 [---]
Cohort 5-year net employment growth rate	-0.88 (7.54)	0.39** [0.004]	0.31* [0.026]	-0.28* [0.040]
Net employment growth rate of survivors only	26.3 (8.11)	0.54** [0.000]	0.44** [0.001]	-0.44** [0.001]
Cohort wage growth rate	20.4 (6.37)	0.60** [0.000]	0.56* [0.000]	-0.07 [0.606]
Entrant initial wage/MSA wage	0.54 (1.15)	-0.04 [0.765]	-0.13 [0.335]	-0.13 [0.336]
Entrant 5th-year wage/MSA wage	0.83 (1.15)	0.52** [0.000]	0.40** [0.003]	-0.21 [0.138]

N = 53

NOTES: RESULTS ARE THE PEARSON CORRELATIONS OF THE LISTED VARIABLE WITH THE ON THE NET EMPLOYMENT GROWTH RATE. VARIABLES REPRESENT STATISTICS FOR A POOLED SAMPLE OF ENTRANTS IN 53 MSA'S. THE SAMPLE MEANS (AND STANDARD DEVIATIONS) ARE UNWEIGHTED ACROSS THE MSA'S. "MSA NET GROWTH" REFERS TO THE MEAN NET EMPLOYMENT GROWTH RATE OF THE MSA; "ENTRANT SHARE" REFERS TO THE ENTRANT'S SHARE OF MSA ESTABLISHMENTS; AND "EXIT AGE" REFERS TO THE AVERAGE ESTABLISHMENTS' AGE AT WHICH EXIT OCCURS.
** DENOTES SIGNIFICANCE AT THE 1 PERCENT LEVEL. * DENOTES SIGNIFICANCE AT THE 5 PERCENT LEVEL.

TABLE 8.
METROPOLITAN AREA EDUCATION AND AGE STATISTICS –
GROUPED BY EMPLOYMENT GROWTH

	Persons 25 Years and Older		
	Share with at least a high school degree	**Share with at least a bachelor's degree**	**Share of Population 25 Years and Older**
Sample mean	83.2	25.0	65.5
Across-MSA Correlation with…			
Employment Growth	0.41 [0.002]	0.61 [0.000]	-0.44 [0.001]
Job Reallocation	0.43 [0.002]	0.36 [0.008]	-0.50 [0.000]
Average Establishment Age	-0.50 [0.000]	-0.77 [0.000]	0.41 [0.002]

Notes: Statistics are author's tabulations from the SF-3 sample of the 2000 decennial census. The table reports the sample means with Pearson Correlations across the 53 MSA's and their *p*-values. All correlations are significant at the 1 percent level.

TABLE 9.
STATE GROWTH, REALLOCATION, AND UNION STATISTICS

State	**Employment Growth**	**Job Reallocation**	**Share of Workers in a Union**
Colorado	1.13	15.5	9.7
North Carolina	0.83	13.5	4.1
Michigan	0.54	14.3	24.0
Ohio	0.50	13.9	19.5
Pennsylvania	0.38	13.4	17.7

Notes: Employment growth and job reallocation are average quarterly rates for March 1992 to March 2000 calculated from the LDB sample of establishments. Union membership is for 1996 and comes from U.S. Bureau of the Census (1998), p. 23.

TABLE A.1. METROPOLITAN AREA QUARTERLY STATISTICS – ALL METROPOLITAN AREAS, LISTED BY EMPLOYMENT GROWTH

Metropolitan Area	Employment Growth	Wage Growth	Employment (thousands)	Wages (1992 $)	Job Creation	Job Destruction	Job Reallocation	Average Establishment Size	Average Establishment Age
Fort Collins-Loveland, CO MSA	1.38	0.57	81	5,702	9.2	7.8	16.9	15.3	40.6
Boulder-Longmont, CO PMSA	1.34	1.30	123	7,231	8.2	6.9	15.1	16.4	38.9
Greeley, CO PMSA	1.27	0.30	49	5,372	9.1	7.8	16.9	17.3	44.8
Colorado Springs, CO MSA	1.23	0.51	170	5,880	8.6	7.4	16.0	18.0	41.3
Raleigh-Durham-Chapel Hill, NC MSA	1.15	0.91	465	6,525	7.6	6.5	14.1	18.9	38.7
Grand Junction, CO MSA	1.13	0.02	36	4,894	9.1	8.0	17.1	14.8	43.1
Greenville, NC MSA	1.12	0.18	43	4,863	9.1	8.0	17.0	17.6	41.0
Wilmington, NC MSA	1.09	0.19	77	5,266	9.3	8.2	17.5	13.9	38.7
Denver, CO PMSA	1.06	0.78	855	7,192	8.1	7.1	15.2	17.7	42.0
Jacksonville, NC MSA	1.00	0.30	24	3,531	9.0	8.0	17.1	12.4	40.7
Charlotte-Gastonia-Rock Hill, NC-SC MSA	0.92	0.84	636	6,646	7.3	6.4	13.6	19.7	42.2
Pueblo, CO MSA	0.85	0.18	40	4,786	8.0	7.2	15.2	17.1	49.1
Grand Rapids-Muskegon-Holland, MI MSA	0.83	0.43	462	6,300	7.3	6.4	13.7	22.3	44.0
Fayetteville, NC MSA	0.80	0.23	72	4,728	7.9	7.1	14.9	16.7	43.6
Columbus, OH MSA	0.78	0.51	643	6,226	7.61	6.8	14.4	20.3	40.3
Hamilton-Middletown, OH PMSA	0.77	0.34	97	6,205	7.5	6.7	14.1	17.9	41.5
Asheville, NC MSA	0.72	0.20	86	5,185	7.4	6.7	14.2	17.2	43.0
Goldsboro, NC MSA	0.68	0.34	33	4,549	7.3	6.6	13.9	17.4	47.7
Jackson, MI MSA	0.61	0.24	47	6,090	7.3	6.7	13.9	17.0	48.9
Ann Arbor, MI PMSA	0.59	0.83	212	6,988	7.4	6.8	14.1	19.7	40.6
Greensboro-Winston Salem-High Point, NC MSA	0.57	0.38	543	5,892	6.4	5.8	12.1	21.0	44.6
Toledo, OH MSA	0.55	0.43	259	6,054	7.5	6.9	14.4	19.3	45.9
Detroit, MI PMSA	0.55	0.81	1,742	8,050	7.6	7.0	14.6	20.2	43.7
Cincinnati, OH-KY-IN PMSA	0.53	0.84	670	6,640	7.3	6.8	14.1	19.7	41.6
Harrisburg, PA MSA	0.52	0.33	261	6,025	6.5	6.0	12.7	20.9	44.6
Akron, OH PMSA	0.51	0.25	264	6,286	7.3	6.8	14.1	17.3	44.3
Altoona, PA MSA	0.51	0.26	47	4,869	6.7	6.2	12.9	17.2	46.2

(See notes at end of table.)

TABLE A.1.—CONTINUED

Metropolitan Area	Employment Growth	Wage Growth	Employment (thousands)	Wages (1992 $)	Job Creation	Job Destruction	Job Reallocation	Average Establishment Size	Average Establishment Age
Hickory-Morganton-Lenior, NC MSA	0.49	0.42	153	5,087	5.5	5.0	10.5	24.0	47.3
Lancaster, PA MSA	0.49	0.32	185	5,860	6.2	5.7	11.9	20.2	43.8
Sharon, PA MSA	0.47	-0.07	40	5,183	7.2	6.7	13.9	16.5	46.6
Canton-Massillon, MSA	0.46	0.23	151	5,631	6.8	6.4	13.2	17.4	46.9
Lansing-East Lansing, MI MSA	0.45	-0.13	157	6,171	7.3	6.8	14.1	18.7	43.7
Lima, OH MSA	0.42	0.31	64	5,693	6.9	6.4	13.3	19.0	50.0
York, PA MSA	0.42	0.29	141	6,014	6.4	6.0	12.3	20.7	45.3
Cleveland-Lorain-Elyria, OH PMSA	0.41	0.44	945	6,676	7.0	6.6	13.5	17.8	44.8
Philadelphia, PA-NJ PMSA	0.40	0.40	1,877	7,331	7.1	6.7	13.8	17.9	42.3
State College, PA MSA	0.39	0.26	40	4,913	7.6	7.2	14.8	15.7	42.3
Erie, PA MSA	0.37	-0.02	110	5,661	6.7	6.3	13.0	19.1	47.1
Dayton-Springfield, OH MSA	0.35	0.35	383	6,346	6.9	6.6	13.5	20.0	44.9
Reading, PA MSA	0.34	0.28	141	6,320	6.5	6.1	12.6	20.1	47.1
Williamsport, PA MSA	0.34	0.17	45	5,087	6.2	5.9	12.1	18.0	48.0
Allentown-Bethlehem-Easton, PA MSA	0.34	0.24	227	6,385	6.9	6.5	13.4	18.3	45.2
Scranton--Wilkes-Barre--Hazelton, PA MSA	0.34	0.27	231	5,192	7.0	6.6	13.6	17.9	44.9
Saginaw-Bay City, MI MSA	0.33	0.52	146	6,910	6.6	6.3	12.9	18.9	45.4
Kalamazoo-Battle Creek, MI MSA	0.32	0.26	174	6,260	7.4	7.1	14.4	20.7	46.4
Pittsburgh, PA MSA	0.32	0.42	903	6,463	6.9	6.6	13.5	18.0	46.6
Benton Harbor, MI MSA	0.27	0.63	59	5,808	7.9	7.7	15.6	17.4	47.1
Youngstown-Warren, OH MSA	0.24	0.17	207	5,823	7.2	7.0	14.2	16.7	46.3
Mansfield, OH MSA	0.23	0.27	67	5,414	7.0	6.8	13.8	18.5	49.5
Johnstown, PA MSA	0.21	0.01	69	4,714	7.0	6.7	13.7	14.6	48.7
Flint, MI PMSA	0.19	0.06	147	7,520	7.1	6.9	13.9	20.1	43.2
Rocky Mount, NC MSA	0.16	0.42	56	5,249	7.36	7.2	14.6	21.1	47.0
Steubenville-Weirton, OH-WV MSA	0.00	0.00	42	5,887	6.4	6.4	12.9	15.9	47.7

Notes: Statistics are for March 1992 to March 2000. See the note for table 3 for details on these statistics.

Table A.2.
MSA Growth Interactions with the Age-Job Flow Relation for Entrants

AGE	DEPENDENT VARIABLE: JOB REALLOCATION RATE	JOB CREATION RATE	JOB DESTRUCTION RATE
1 QUARTER	7.868**	7.148**	0.719*
2 QUARTERS	3.478**	2.636**	0.842**
3 QUARTERS	2.987**	2.380**	0.607
4 QUARTERS	1.808**	0.754**	1.055**
5 QUARTERS	1.702**	1.452**	0.250
6 QUARTERS	2.175**	2.220**	-0.045
7 QUARTERS	1.510**	0.684*	0.826**
8 QUARTERS	1.125**	0.607*	0.518
9 QUARTERS	1.818**	1.328**	0.490
10 QUARTERS	1.073**	0.567	0.506
11 QUARTERS	1.409**	0.663*	0.745*
12 QUARTERS	1.188**	0.500	0.688
13 QUARTERS	1.756**	1.469**	0.287
14 QUARTERS	0.282	0.611*	-0.329
15 QUARTERS	0.671	-0.058	0.729*
16 QUARTERS	0.921*	0.095	0.826**
17 QUARTERS	-0.040	0.771**	-0.811*
18 QUARTERS	-0.799	0.326	-1.125**
19 QUARTERS	-0.819	-0.112	-0.706
R^2	0.384	0.547	0.031

NOTES: ESTIMATES ARE COEFFICIENTS ON THE INTERACTION OF THE MEAN MSA GROWTH RATE WITH ESTABLISHMENT AGE. THEY COME FROM THE EMPLOYMENT-WEIGHTED ESTABLISHMENT-LEVEL REGRESSIONS OF THE LISTED VARIABLE ON THE ABOVE INTERACTIONS, YEAR OF ENTRY EFFECTS, ESTABLISHMENT AGE EFFECTS, 4-DIGIT INDUSTRY EFFECTS, AND THE MEAN GROWTH RATE OF THE ESTABLISHMENT'S MSA. REGRESSIONS USE 2,472,713 QUARTERLY OBSERVATIONS ON 177,373 ACTIVE ESTABLISHMENTS ENTERING IN THE SECOND QUARTERS OF 1993, 1994, AND 1995.

** DENOTES SIGNIFICANCE AT THE 5 PERCENT LEVEL. * DENOTES SIGNIFICANCE AT THE 10 PERCENT LEVEL.

Figure 1.
Job Reallocation by Age Category, All Metropolitan Areas

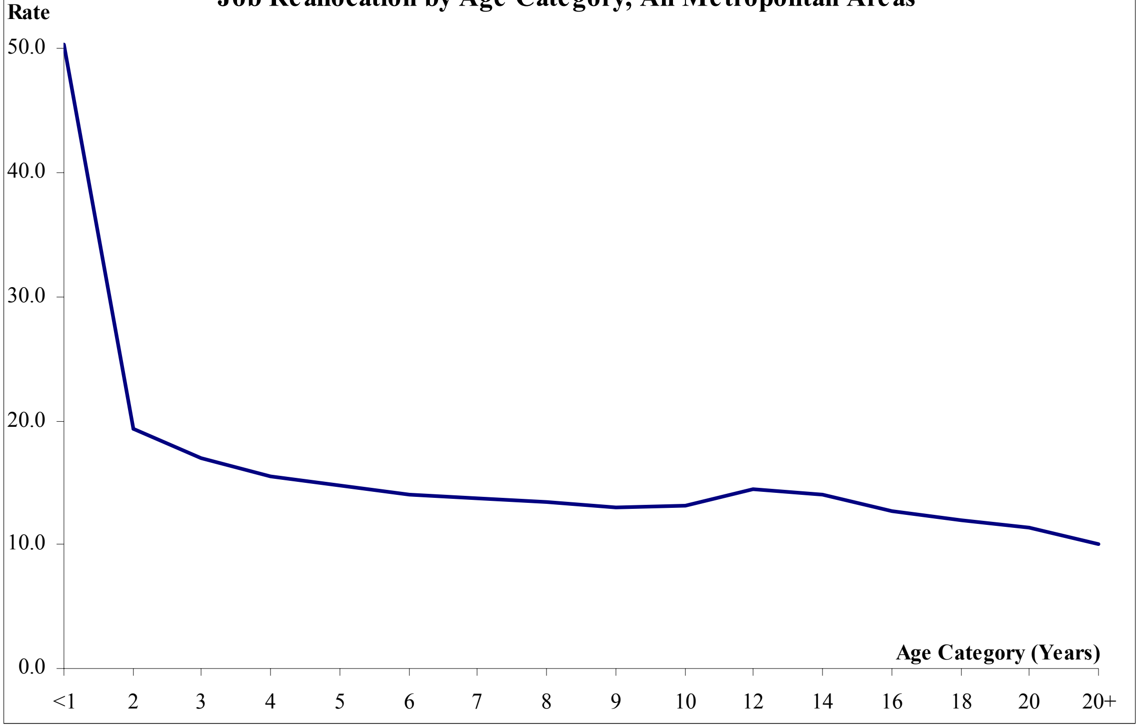


Figure 2.
Employment Distributions by Age Category, All Metropolitan Areas

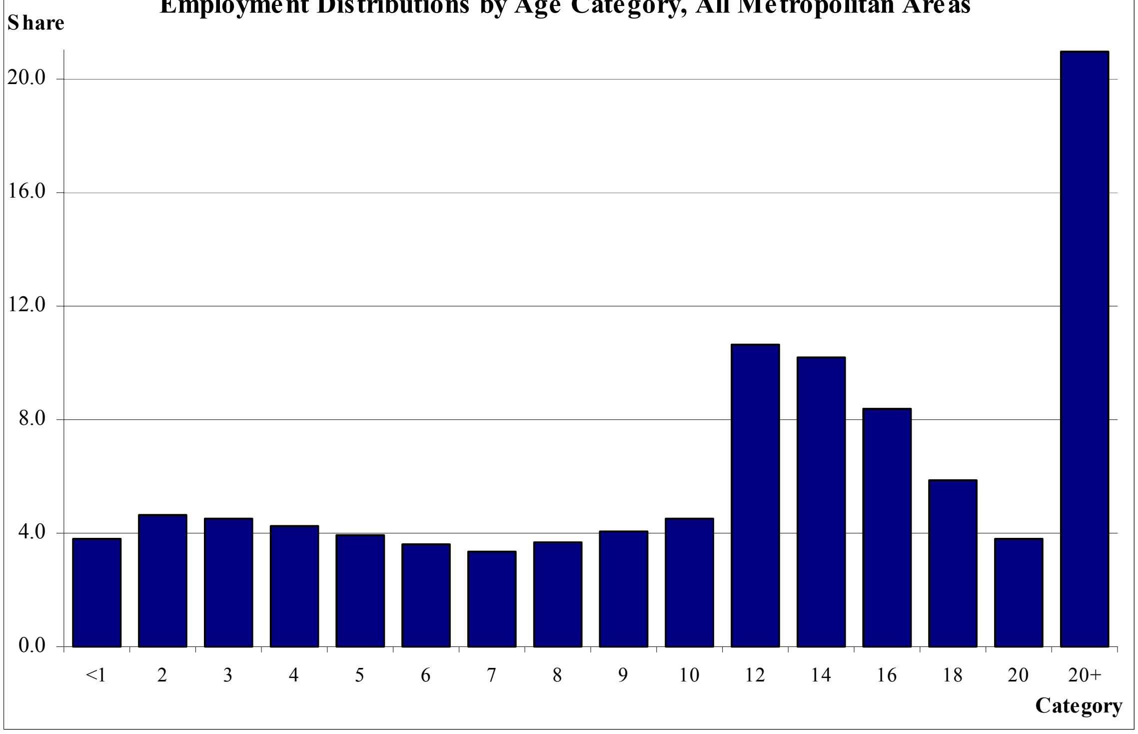


Figure 3.
Reallocation and Age - MSA Interactions, No Industry Effects

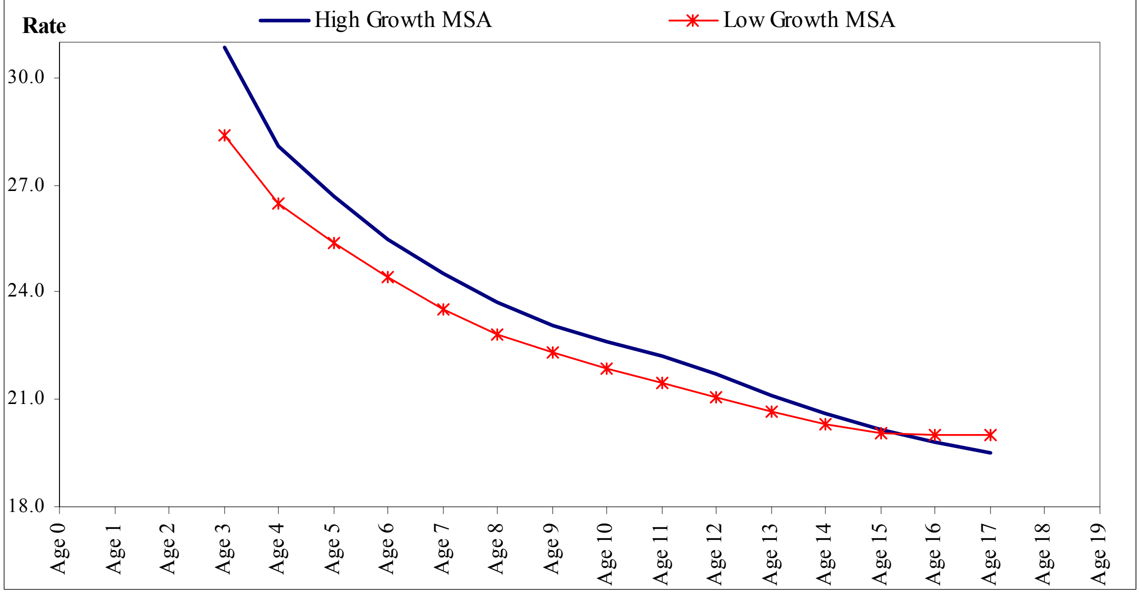


Figure 4.
Reallocation and Age - MSA Interactions and Industry

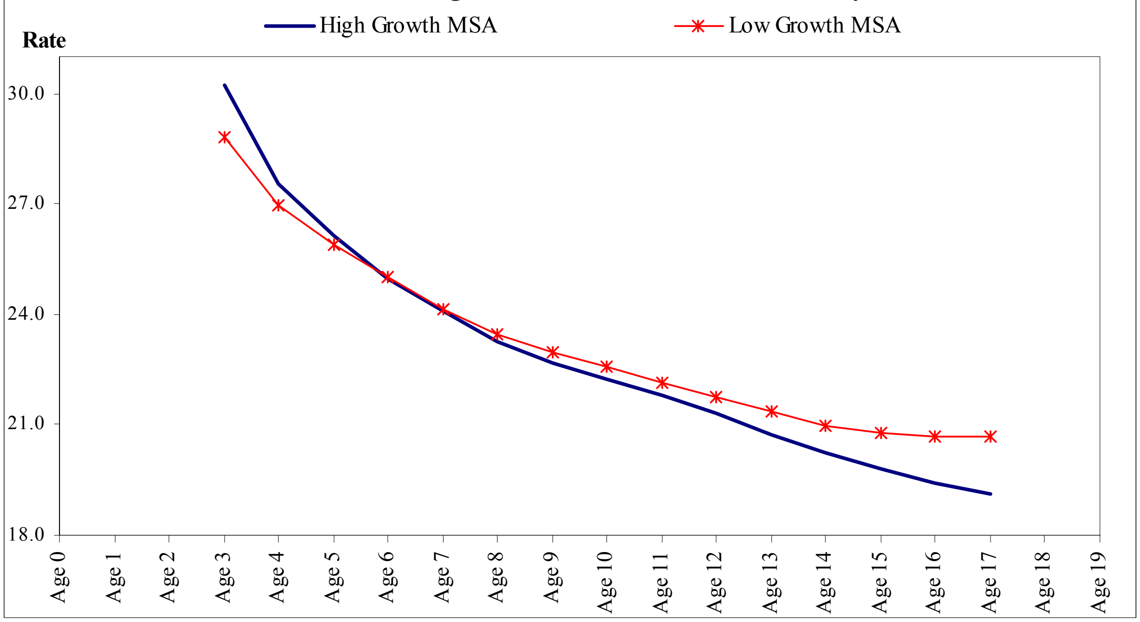


Figure 5.
Job Creation and Age - MSA Interactions and Industry

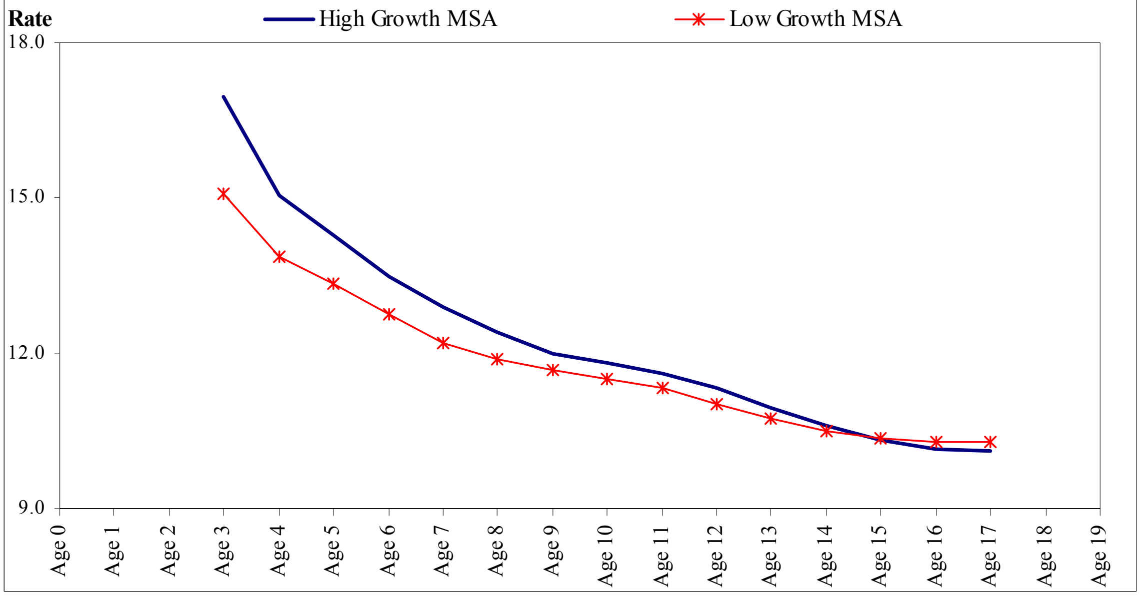


Figure 6.
Job Destruction and Age - MSA Interactions and Industry

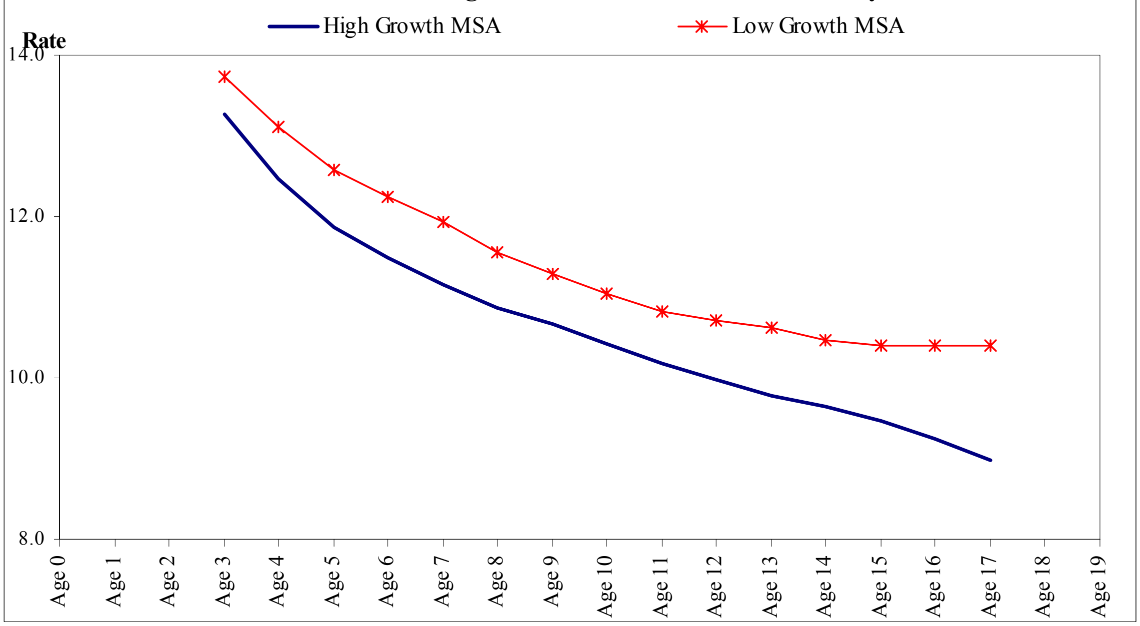
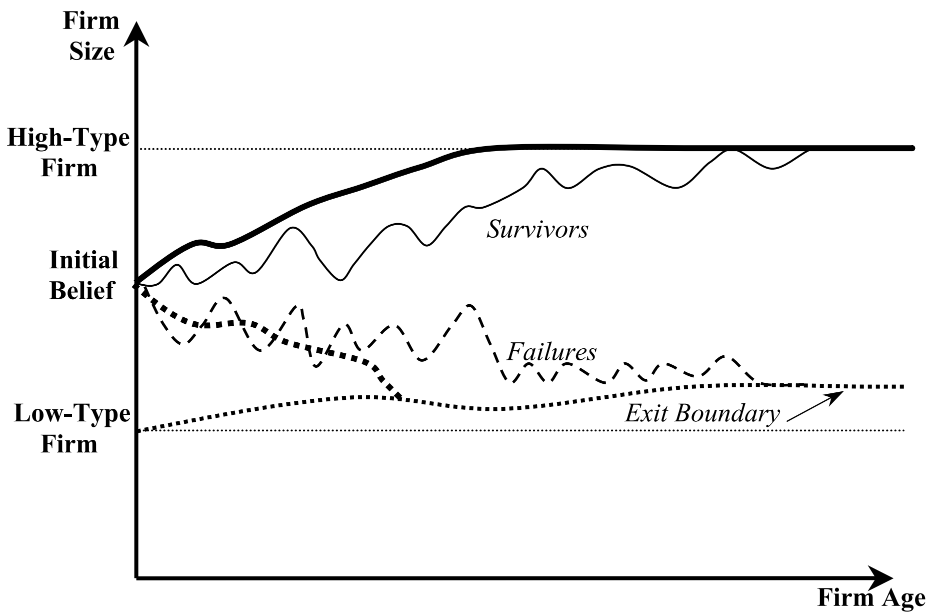


Figure 7.
Evolution of Firm Beliefs in Two Environments of Differing Signal Noise



Notes: The thick solid and dashed lines represent the size paths of a productive and less productive firm, respectively, in an environment with little signal noise. The thin solid and dashed lines represent the size paths of a productive and less productive firm, respectively, in a noisy learning environment. The thick dotted line represents the threshold at which firms will no longer find it profitable to operate.